The Causal Effect of Educational Attainment on Wages and Employment Among Early-Career Adults

Evidence from 2021 Canadian Census

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Abstract

"Does more education always lead to better job outcomes?" This paper investigates the causal effect of educational attainment on wages and employment among early-career adults in Canada, using 2021 Census data. A two-stage least squares (2SLS) approach is applied, with "moved for education" serving as the instrumental variable to predict education attainment. A semi-parametric function is used to flexibly approximate these relationships across predicted education levels. Wages, modeled in logarithmic form, increase monotonically with education, showing the largest jump at the Master's level. Employment probabilities, estimated via logistic regression, reveal a more uneven pattern, with dips at certain advanced degrees. These findings support common socioeconomic views that education enhances earning potential, but challenge the assumption that higher education guarantees better employment outcomes.

1. Introduction and Motivation

The level of post-secondary educational attainment is a critical question for many young adults. Not only is university tuition costly and often associated with substantial debt, but the opportunity cost of time—years spent studying instead of earning income or gaining work experience—also plays a significant role in the decision-making process. This makes it essential to understand whether higher education translates into tangible economic benefits, such as increased wages or improved employment prospects. Many people assume that higher education automatically leads to better wages and improved employment outcomes. While this association is often supported by descriptive statistics, the key question remains: **is this relationship causally true**? In other words, do individuals earn more *because* they attain higher education, or are there other underlying factors—such as motivation, family background, or innate ability—that drive both educational attainment and labor market success?

While most traditional views and existing studies emphasize the importance of education in improving future income, recent critiques—including works such as Charlie Kirk's *The College Scam*—have raised skepticism about the financial returns of higher education, arguing that the traditional college model may no longer deliver on its economic promises. These arguments often highlight the rising cost of tuition, the burden of student debt, and the mismatch between degrees and labor market demands, suggesting that the return on investment for a university education may be overstated or uneven across fields and individuals. In fact, the author argues that alternatives such as certificate or diploma programs, and trade schools may offer a more practical and financially beneficial path for many individuals, especially when compared to the high cost and uncertain payoff of a traditional bachelor's degree.

Given the controversy surrounding the value of higher education, this paper aims to answer a key question faced by many teenagers and young adults: How do different levels of post secondary education attainment affect wages and employment outcomes? This study uses data from the 2021 Canadian Census, focusing on early-career adults aged 25 to 40, examining their employment outcomes in relation to their educational attainment. Unlike studies that rely solely on correlations, this paper employs an Instrumental Variable (IV) approach to estimate the causal effect of education, helping to isolate its impact from confounding factors from measureable socioeconomic background. While many studies focus on the number of years of schooling within compulsory education systems, they often overlook the distinctions between different levels of post-secondary education, such as certificates, bachelor's, and master's degrees. This study aims to address that gap by investigating the differential impacts of post-secondary attainment levels.

2. Literature Review

The two sides of this topic are fairly clear. On one hand, many economists argue that additional schooling leads to higher income. On the other hand, critics suggest that the returns to education vary significantly depending on individual characteristics and broader contextual factors.

In "*Does Compulsory School Attendance Affect Schooling and Earnings?"* (Angrist & Krueger, 1991), the authors use quarter of birth (Q.O.B) as an instrumental variable to estimate the causal effect of education on earnings, using U.S. Census data. Students born later in the year tend to start school at an older age and remain enrolled longer due to compulsory schooling laws. Since Q.O.B. likely influences earnings only through its effect on schooling, it serves as a valid instrument. Their findings suggest that each additional year of schooling increases earnings by approximately 7–10%. A similar approach is used in the Canadian context. In "*Estimating Average and Local Average Treatment Effects of Education When Compulsory Schooling Laws Really Matter"* (Oreopoulos, 2006), the author exploits changes in minimum school-leaving ages across Canadian provinces and cohorts as a natural experiment. Using a regression discontinuity design that mimics an instrumental variable strategy, the study estimates that an additional year of schooling raises earnings by about 15%.

However, not all studies support the notion that more education always yields higher returns. In "*Returns to Education: The Causal Effects of Education on Earnings, Health, and Smoking"* (Heckman, 2006), the author employs a structural econometric model to show that the returns to education are highly heterogeneous. For individuals with limited cognitive or non-cognitive skills, the returns may be low—or even negative—suggesting that education is not beneficial for everyone. Similarly, *Returns to Education in Developing Countries* (Banerjee, 2005) uses natural experiments and IV strategies to demonstrate that returns to education vary substantially by region, gender, and socio-economic status. In some cases, additional schooling produces minimal labor market gains. These studies emphasize the importance of recognizing variation in individual capacity and institutional context when assessing the value of education as an economic investment.

In conclusion, while some studies suggest that additional years of education lead to higher income and employment odds, others emphasize the highly heterogeneous returns to education—not everyone benefits from a higher level of education. Factors like cognitive ability and socioeconomic background may introduce selection bias, with gains favoring already high-achieving individuals. This study aims to isolate the causal effect of educational attainment on employment and wages, while controlling for socioeconomic background. We do not address opportunity costs or the financial burden of student debt.

3. Data and Methodology

3.1 Research Question and Hypothesis

Building on the contrasting perspectives discussed in the literature, this paper aims to identify the causal impact of different levels of post-secondary educational attainment on wages and employment outcomes.

- Research question: *What is the causal impact of different levels of post-secondary educational attainment on employment status and wages among early-career adults in Canada?*

H_0 : Wages and Employment rates **are strictly increasing** by post-secondary education attainment

H_A : Wages and Employment rates **are not strictly increasing** by post-secondary education attainment

In this study, we define "strictly increasing" returns to post-secondary education as a pattern in which higher levels of educational attainment consistently lead to better labor market outcomes. Specifically, this means that individuals with a bachelor's degree should, on average, earn higher wages and have higher employment rates than those who have completed only a 1–2 year college diploma or certificate program. In turn, those with a certificate should perform better in the labor market than individuals whose highest level of education is a high school diploma. This framework assumes a clear ranking in returns based on the level of education completed, with no overlap or reversal in outcomes across categories.

The null hypothesis reflects the perspective of traditional human capital theory, which assumes that additional education consistently leads to improved labor market outcomes. Under this view, each successive level of education should yield higher earnings and employment rates—for instance, a PhD graduate is expected to earn more, on average, than a master's graduate, who in turn should outperform someone with only a bachelor's degree, and so on.

The alternative hypothesis, on the other hand, suggests that returns to education may exhibit dips or irregularities at certain levels. For instance, it is possible that individuals with a master's degree earn more, on average, than those with a PhD, or that graduates of trade schools may have better employment outcomes than those who completed a two-year college diploma. Such outcomes would challenge the assumption of a clear upward trajectory in returns and instead highlight the possibility of heterogeneous or context-specific effects across different types of educational pathways.

3.2 Data Sources and Key variables

This study utilizes individual-level cross-sectional data from the 2021 Canadian census, as provided through the course materials. An instrumental variable (IV) design is estimated using two-stage least squares (2SLS), which helps address the endogeneity concerns inherent in ordinary least squares estimation and supports a more robust causal interpretation of the effect of education on labor market outcomes. The following section outlines the variables used in the analysis, along with the specific filters and value selections applied to the 2021 Canadian census data.[1]

Filter Conditions

To ensure the relevance and reliability of our analysis, we apply the following filters to the dataset:

- Age Range: The sample is *restricted to individuals aged 25 to 40*, corresponding to age bins 9–11, to focus on those in the early stages of their careers.

- Labour Market Participation: Only individuals who are *active in the labour market* are included—specifically, those who are employed or actively seeking employment. Individuals who are retired, studying, or not seeking work are excluded.

- Non-Missing Values: Observations are retained only if the individual has complete data for all key variables, including the treatment, outcome, and control variables, to ensure consistency in the regression analysis.

Control Variables:

\`agegrp\` (Categorical): represents the respondent's age group. Age may influence both employment outcome and education attainment, as individuals at different life stages face varying labor market dynamics.

\`gender\` (Binary): Indicates the respondent's gender, where 1 = female and 2 = male. Gender is included as a control variable to account for systemic differences in both educational attainment and labour market outcomes between males and females.

\`CFInc\` (Categorical): Denotes the respondent's total family income category. Controlling for family income helps account for socioeconomic background, which may affect educational attainment, wages and employment.

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[1] See appendix 3 for the references to the 2021 Canadian Census data

`pr’ (Categorical): Refers to the province of residence. This controls for regional variation in labor markets, as different provinces may have different wage levels, job opportunities, post-secondary schools and economic conditions.

‘Citizen` (Categorical): Indicates whether the respondent is a Canadian citizen. Citizenship status is controlled to account for potential differences in both educational attainment and labor market outcomes. Citizens may have greater access to post-secondary education due to lower tuition fees, eligibility for government financial aid, and fewer administrative barriers.

Treatment and Outcome Variables:

- `hdgree` (Continuous): Highest Degree Attained**,** this is our main treatment variable. Although the gaps between education levels aren't equal, we treat it as numeric to simplify the model and capture the ordinal progression of education and its link to labour market outcomes.

- `Wages` (Continuous): This outcome variable measures annual gross wages and salaries before deductions (e.g., income tax, pension contributions, and EI premiums) during the reference period. It reflects the employment returns to education.

- `lfact` (Binary) : Employment Status, A binary outcome variable indicating whether the individual is employed (1) or unemployed (0) during the reference period.

3.3: Instrumental Variable and Validity of Conditions

To estimate the causal effect of educational attainment on wages, our chosen instrumental variable is whether an individual **"Moved for education".** The idea is that many individuals move away from their hometowns to pursue a higher level of education, often relocating to regions with better post-secondary institutions. These moves are typically motivated by limited access to advanced education opportunities locally. As a result, whether someone moved for education purposes serves as a strong predictor of higher educational attainment, making it a plausible instrument in our IV framework. The following reasons are how this variable satisfies the condition of IV.

- **Exogeneity (Independence Assumption):** The decision to move far away from home for education is assumed to be unrelated to unobserved factors that influence an individual's potential wage, employment status, or education level. In other words, knowing a person's potential outcomes does not help predict whether they moved for the purpose of pursuing higher education.

- **Exclusion:** After accounting for differences in provincial labor markets and wages, moving to a different province should not directly affect an individual's wage or employment status — except through its impact on educational attainment. In other words, conditional on provincial factors, the act of moving for education is assumed to influence labor market outcomes only by increasing one's level of education, not through other direct channels.

- **Monotonicity:** We assume that individuals who move away from their home region to pursue education do so because higher education opportunities are unavailable or less desirable locally. In this context, moving for education either increases or does not affect one's likelihood of attaining higher education, but it never decreases it. That is, there are no individuals for whom moving would make them less likely to pursue further education. This is a reasonable assumption, as it is unlikely that individuals would go through the effort and cost of relocating in order to access a lower-quality or less accessible educational opportunity.

This variable is not directly available in the census data but is inferred using information from respondents' mobility and education history. Specifically, we identify individuals who likely moved away from their home region to pursue higher education opportunities through the following method

- \`Moved_for_studying\` = \`Different_study_location\` * \`Moved_in_5_years\`

where \`Different_study_location\` and \`Moved_in_5_years\` are binary variables identifying interprovincial movers. Therefore the IV itself is also binary with 1 = movers and 0 = non-movers.

- <u>\`Different_study_location\`</u>: One if the variable \`LOC_ST_RES\` (Location of study) is in another province or outside of canada. Zero otherwise
- <u>\`Moved_in_5_years\`</u>: One if the variable \`Mob5\` is interprovincial migrants or international migrants.

The logic is that individuals who moved provinces within the past five years and also reported studying in a different province than their current residence are likely to have relocated for educational purposes. This constructed variable serves as a proxy for identifying education-motivated migration in the absence of a direct question in the census data. Although some may argue that individuals could have moved for work or better wages rather than education, we address this concern by controlling for provincial differences in wages and employment rates. This helps reduce bias from economic-driven migration unrelated to education.

**Given the length and detail of the categorical breakdowns, the summary table of categorical, continuous variables with education bins are presented in the appendix 1 for reference.*

3.4: Potential Outcome framework and Empirical Model Specification

Here we are going to specify our model for estimating the causal effect of educational attainment on labour market outcomes. We focus on two main outcomes: annual wages and employment status. To estimate the causal effect of education, we employ a Two-Stage Least Squares (2SLS) instrumental variable approach.

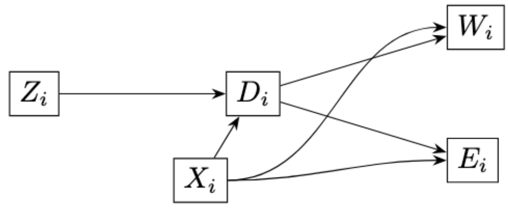
Z_i : Whether if someone moved for education 1 = yes, 0 = no (Instrument)

D_i : Highest level of education attainmnet (Treatment)

W_i : Annual Wages in CAD (Outcome)

E_i : Employment status, 1 = employed, 0 = unemployed (Outcome)

X_i: The set of control variables from 3.3



$Z_i \to D_i$: Levels of education attainment is influence by their decision to moved for better education.

$D_i \to W_i$: Education attaiment affect wages

$D_i \to E_i$: Eudcaiton attainment affect their employment status.

$X_i \to E_i, W_i, D_i$: Observed covariates affect both the treatment and outcomes

Figure 3.1: Potential outcome and Causal Diagram

In this framework, each individual has potential outcomes $W_i(d)$ and $E_i(d)$, representing wages and education under different levels of educational attainment d . However, the observed education level D_i may be endogenously determined by unobserved factors such as motivation and intelligence. To address this, we control for a set of observable covariates X_i and introduce an instrumental variable Z_i that influences D_I but is independent of W_i and E_i conditional on the covariates. This allows us to recreate a quasi-random assignment process, approximating how individuals would be sorted into different education levels given their observed characteristics. The result from the empirical model provides the Local Average Treatment Effect (LATE), which captures the change in employment outcomes due to educational attainment for individuals who were induced to pursue more education as a result of moving for schooling. The following is the condition for IV design in potential outcome model

- <u>Exogeneity (Independence)</u> : $W_i(d, z)$, $E_i(d, z)$, $D_i(z) \perp Z_i \mid X_i$, the status of their potential treatment and potential market outcome is independent of the IV once we know X_i
- <u>Exclusion:</u> $W_i(d, z) = W_i(d)$ and $E_i(d, z) = E_i(d)$ for all z, outcome is influenced by the instrument through education.
- <u>Monotonicity:</u> $D_i(z') \geq D_i(z)$ for any $z' \geq z$

First stage model:

$$D_i = \pi Z_i + \sum_k \sum_j \delta_{k,j} X_{k,j,i} + \epsilon_i$$

Where $X_{k,j,i}$ is a dummy variable indicating whether individual i falls into the j-th category of the k-th control variable.

Here we account for the possibility that educational attainment is influenced not only by the instrument but also by observed individual characteristics . These controls help isolate the variation in education that is plausibly exogenous. The term pi in front of the IV suggest the change in education level when one has moved to pursue better education. Every delta represents the effect of belonging to a specific subpopulation defined by the j-th category of the k-th control variable. For example, if an individual i is from province Quebec (category j of control k: province), then that specific delta captures the specific shift in predicted education associated with being from province Quebec.

Second stage model - Wages :

In the second stage of the IV regression, we use the fitted values of educational attainment obtained from the first stage, to estimate its effect on log wages.

$$log(W_i) = f(\hat{D}_i) + \sum_k \sum_j \beta_{k,j} X_{k,j,i} + \epsilon_i$$

Where $log(W_i)$ is the natural logarithm of the wage variable

In the second stage of the IV regression, we estimate the effect of educational attainment on individual wages by regressing the log of annual wages on the fitted values of education obtained from the first stage. The function f represents a semi-parametric relationship between education and wages, estimated by binning predicted values of education attainment into discrete categories. It is semi-parametric as we do not assume the shape or structure of the function, but it is approximated by estimates in each bin that are linearly related with each other. This flexible approach allows us to capture potential non-linearities in the returns to education. As before, a full set of control variables is included, and the dependent variable is logged to reduce skewness from the wage data, and interpret coefficients as approximate percentage changes in wages. In the later section after obtaining results from the estimate in each bins, we will have a clear look of what the function will look like.

Second stage model - Employment :

$$logit(\Pr(E_i = 1)) = g(\hat{D}_i) + \sum_k \sum_j \alpha_{k,j} X_{k,j,i} + \epsilon_i$$

Where $logit(\Pr(E_i = 1))$ is log-odds of individual i being employed compare to being unemployed

A similar technique is used to estimate the employment outcome, following the same structure as the previous wage model. In this specification, **α** represents the coefficients for the categorical control variables, and the function *g* captures the semi-parametric relationship between education and employment by binning the predicted education values into discrete categories. The key difference is that, because employment status is a binary variable, we use a logistic regression model to estimate the probability of being employed. Specifically, the model estimates the log-odds of employment as a function of education and other covariates, which is then transformed via the logistic function to yield predicted probabilities between 0 and 1. This allows us to interpret the results in terms of how changes in educational attainment affect the likelihood of being employed compared to unemployed.

4. Results and Economical Interpretations[2]

First Stage Regression Summary (Outcome: Educational Attainment)

	No Controls	**With Controls**
Moved for Study	3.135*** (0.030, t = 105.4, p < 2e-16)	2.744*** (0.032, t = 85.9, p < 2e-16)
Intercept	6.192*** (0.009, p < 2e-16)	6.743*** (0.306, p < 2e-16)
Controls	No	Yes
Num. Obs.	150,869	150,869
R^2	0.069	0.189
R^2 Adj.	0.069	0.188
F	11,110	731.7
RMSE	3.316	3.095

Table 4.1: Estimated Effect of Instrumental Variable on Educational Attainment

In the first-stage regression, *Moved for Study* is strongly and significantly associated with higher educational attainment. Without controls, the instrument yields an F-statistic of 11,110, which drops to 731.7 after adding controls—reflecting its marginal contribution conditional on covariates. Despite the decline, the F-statistic remains well above the conventional threshold, confirming the instrument's strength. On average, individuals who moved for education attained 2.744 more levels of education—roughly equivalent to progressing from a 2-year college program to a bachelor's degree, or from a bachelor's to a master's.

[2] See Appendix 2 for full model estimates. Appendix 3 provides category definitions from the Canadian Census.

Education Level	Without Controls	With Controls
Apprenticeship certificate	0.3165 (p = 0.0271)	0.2737 (p = 0.0416)
Program less than 1 year	0.6115 (p = 1.85e-05)	0.3623 (p = 0.0070)
1-2 year program	0.6399 (p = 7.39e-06)	0.3838 (p = 0.0044)
Program of more than 2 year	0.7862 (p = 3.68e-08)	0.3630 (p = 0.0074)
Certificate/Diploma	0.8675 (p = 1.29e-09)	0.3758 (p = 0.0058)
Bachelor	0.7868 (p = 3.99e-08)	0.4982 (p = 0.0003)
Above Bachelor	0.5740 (p = 6.64e-05)	0.5267 (p = 0.0001)
Degree in Medical Field	0.9241 (p = 2.97e-10)	0.4976 (p = 0.0004)
Master	1.3220 (p < 2e-16)	0.7049 (p = 1.85e-06)
Doctor	1.6474 (p = 6.00e-14)	0.8927 (p = 1.29e-05)
Intercept	9.7814	4.9767
R^2	0.01215	0.2026
Adjusted R^2	0.01209	0.2023
F-statistic	185.6	672.4
Residual Std. Error	1.291	1.160

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4.2: Estimated Effect of predicted educational attainment on log wages

The second-stage regression estimates the relationship between education level and log wages using binned predicted education values. The coefficients represent changes in log wages associated with each level of education, relative to the baseline group—individuals with educational attainment below an apprenticeship certificate. Across both specifications—with and without controls—education is positively associated with higher log wages, and the effect size generally increases with higher levels of attainment. For example, progressing from a 2-year program to a master's degree corresponds to a log wage increase of approximately 1.32 without controls and 0.70 with controls. Since the coefficients are in log terms, they will be exponentiated and converted into percentage changes to facilitate meaningful economic interpretation. The inclusion of control variables significantly improves model fit, increasing the adjusted R^2 from 0.012 to 0.202 and reducing residual error. Once we added control variables, the p-values for several education bins increased. This indicates that the estimated effect of educational attainment on employment becomes less statistically significant when accounting for other factors. It suggests that the control variables—such as age group, income class, gender, or province—not only influence employment outcomes but are also correlated with education level, acting as confounders in the relationship between education and employment. Hence verify our guesses of causal flows in section 3.4.

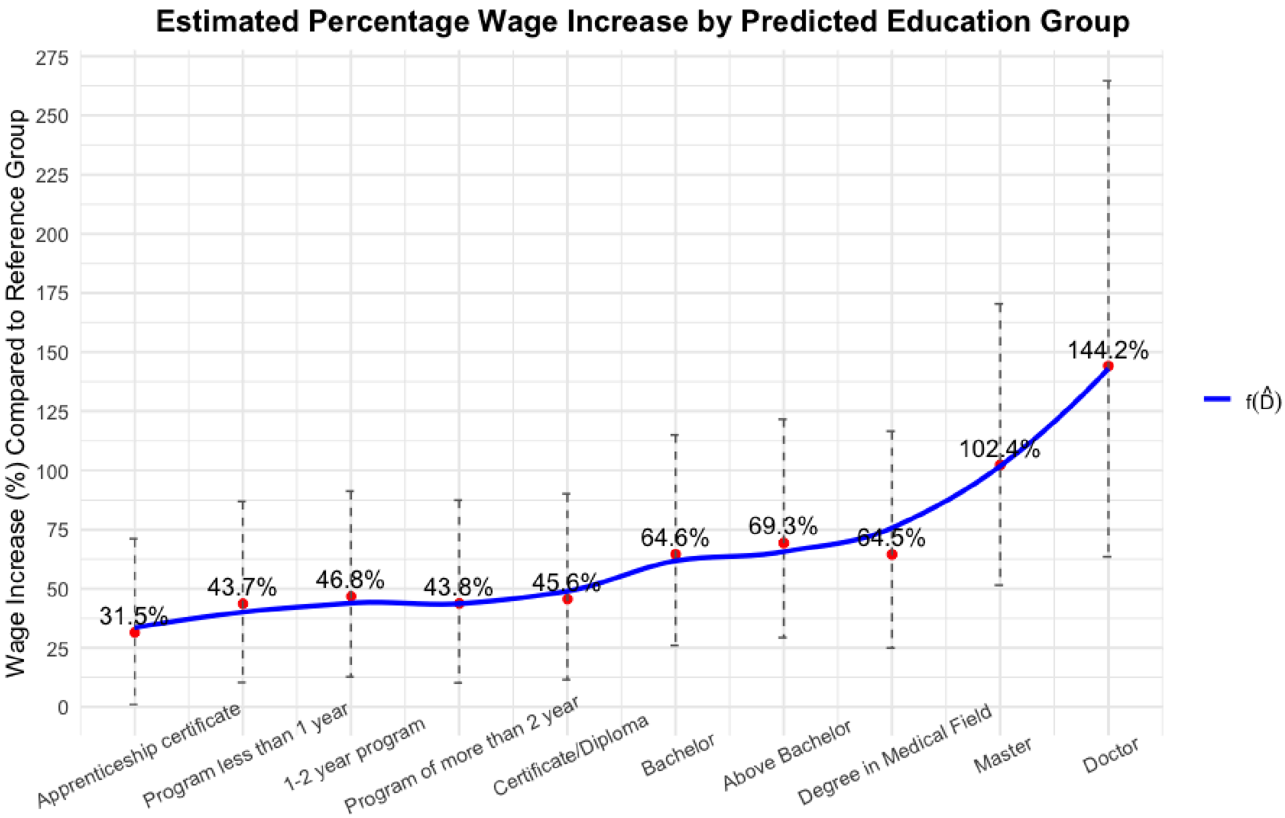


Figure 4.3: LATE of educational attainment on percentage wage increase relative to baseline group

The graph displays estimated percentage wage increases associated with predicted education levels, relative to a baseline group (individuals with education below an apprenticeship certificate). These estimates are derived by exponentiating second-stage regression coefficients and subtracting one to convert log-wage differences into percentage terms. The blue curve, introduced in Section 3.4, captures a flexible functional relationship between education and wages, with error bars representing standard errors.

These results directly address the research question by showing a clear upward trend in returns to education. Individuals predicted to attain a Bachelor's degree earn approximately 64.6% more than those in the baseline group. Wage gains continue to rise at the Master's and Doctorate levels, although these estimates come with wider confidence intervals due to limited representation in the first-stage predictions. Minor dips observed at certain education levels likely reflect random variation rather than systematic effects. By controlling for key covariates and employing a strong instrument, the model provides credible causal evidence linking higher educational attainment to increased wages. On average, wages increase with higher levels of education, with the most pronounced marginal gain occurring when moving from a Bachelor's to a Master's degree.

Education Level	Without Controls (Estimate, p-value)	With Controls (Estimate, p-value)
Apprenticeship certificate	0.2727 (p = 0.369)	0.2086 (p = 0.529)
Program less than 1 year	0.6761 (p = 0.0257)*	0.4847 (p = 0.144)
1–2 year program	0.8454 (p = 0.0053)**	0.6502 (p = 0.052)
Program of more than 2 year	0.9625 (p = 0.0015)**	0.6344 (p = 0.060)
Certificate/Diploma	1.0484 (p = 0.0006)***	0.7016 (p = 0.039)*
Bachelor	1.1358 (p = 0.0002)***	0.9986 (p = 0.0034)**
Above Bachelor	0.9381 (p = 0.0023)**	0.9241 (p = 0.0075)**
Degree in Medical Field	1.1245 (p = 0.0005)***	0.7865 (p = 0.030)*
Master	1.1299 (p = 0.0017)**	0.6040 (p = 0.131)
Doctor	2.4084 (p = 0.0221)*	2.0796 (p = 0.051)

Model Summary

	Without Controls	With Controls
Null Deviance	81304 (df = 150868)	81304 (df = 150868)
Residual Deviance	80781 (df = 150858)	77577 (df = 150811)
AIC	80803	77693

$* p < 0.05$, $** p < 0.01$, $*** p < 0.001$

Table 4.4: Estimated Effect of predicted educational attainment on logit

The above table shows the additional effect on logit value of employment odds from obtaining each level of education compared to the baseline group — individuals whose highest educational attainment is below an apprenticeship certificate. An interesting observation is that, once covariates are accounted for, many estimates that were previously statistically significant become insignificant. For example, the coefficient for “Program less than 1 year” is significant in the uncontrolled model (p = 0.0257), but loses significance after controlling for key covariates such as age group, gender, province, and income class (p = 0.144). This suggests that some of the observed effects of education on employment probability in the uncontrolled model were likely confounded by these factors.

When an estimate is no longer statistically significant in the controlled model, it implies that we do not have sufficient evidence to conclude that the employment odds for that education level differ from those in the baseline group once these covariates are taken into account. Following this logic, although individuals with Master’s or Doctorate degrees tend to earn significantly higher wages, these advanced degrees do not necessarily guarantee higher employment probabilities. However, it is important to note that the sample sizes for the Master’s and Doctorate groups are relatively small, which may contribute to the wider confidence intervals and reduce the precision of these estimates.

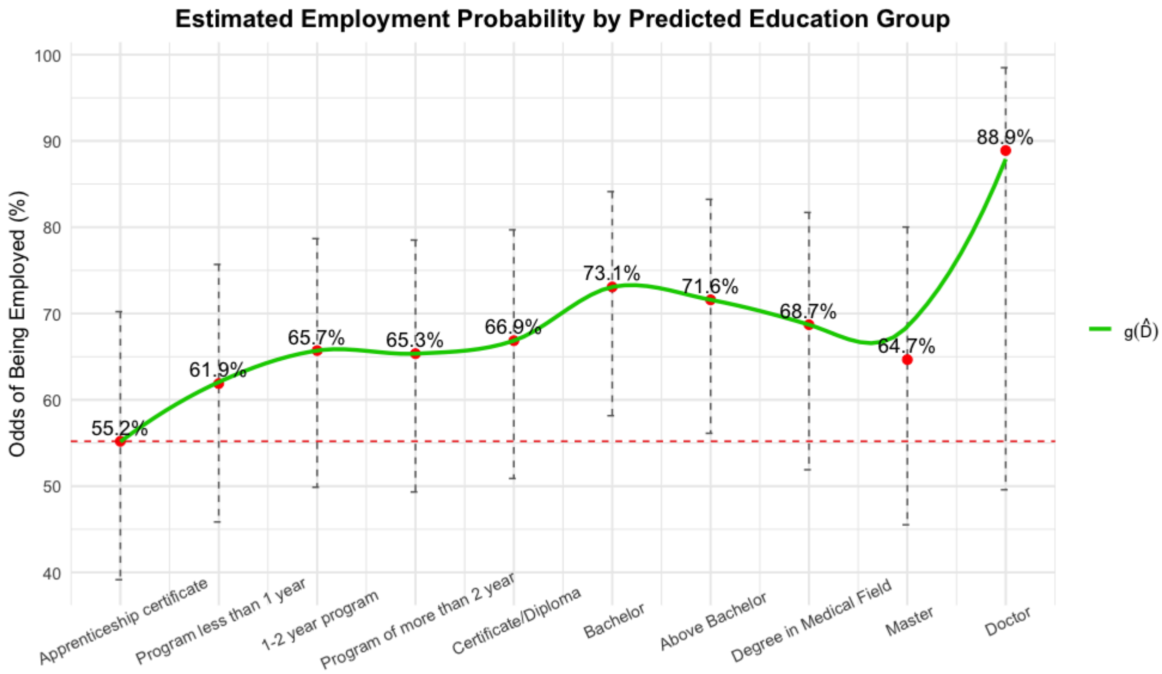


Figure 4.5: LATE of educational attainment on employment odds

The graph above is transformed from estimate of logit into probabilities. The graph reveals several notable patterns. The green line represents the approximation of the semi-parametric function introduced in Section 3.4, while the red horizontal line marks the employment rate of the baseline group. The x-axis displays predicted education groups in ascending order, and the y-axis represents the predicted probability of being employed. Red dots indicate point estimates, and the vertical dashed bars show the corresponding confidence intervals.

Unlike the smooth upward trend observed in wage outcomes, the estimated employment probabilities do not follow a strictly increasing pattern. Although there is a general rise from lower education levels to the Bachelor's level, the function flattens and even dips between the Bachelor's and Doctorate groups. The predicted employment rate for Master's degree holders is noticeably lower than several lower education groups. The Doctorate group, in contrast, shows a sharp upward jump, reaching the highest employment probability among all categories. Additionally, the confidence intervals are wider for higher education groups, especially at the Master's and Doctorate levels, indicating greater uncertainty in those estimates.

The confidence intervals in the graph represent uncertainty around predicted employment probabilities, while the regression table tests differences in log-odds relative to the baseline group. Since these are on different scales and reflect different types of inference, non-overlap with the baseline line in the graph does not always imply statistical significance in the regression table and vice versa.

Social Economical Interpretations

Based on the table and the graphs above, here is the summary of the key findings.

"Wages fluctuate slightly across education levels but follow a generally increasing trend, with the largest gain seen when moving from a university degree to a Master's."

"Employment rates, on the other hand, fluctuate across education levels and do not consistently increase with higher educational attainment."

Hence, it is important to consider possible economic explanations for these patterns. Here are the possible reasons why we observe such trends in wages and employment rate.

Trend in wages

1. *Human Capital theory* : Higher education is associated with increased productivity and specialized skills. Employers pay more to attract and retain individuals with scarce, advanced human capital—especially at the graduate level.
2. *Social Norms and Institutional Structures*: In many sectors, wages are formally or informally tied to educational attainment. It is often expected, or even required by pay grids, to offer higher wages to those with more advanced degrees.
3. *Downward Wage Stickiness:* Employers are reluctant to offer lower wages to highly educated workers, even when the job may not require their full qualifications. At the same time, these individuals may be more selective in their job offers, preferring to wait for wages that they believe are equally matched with their skillset.

Together, these factors help explain why wages are less likely to decrease for individuals with higher education levels. In contrast, the following points offer possible explanations for fluctuations in employment rates across different education levels.

Trend in employment rates

1. *Labor Demand and Job Availability:* Employment rates are influenced not just by education, but by the availability of jobs that match specific qualifications. If there is limited demand for highly specialized roles, individuals with advanced degrees may face lower employment rates despite their credentials.
2. *Education–Job Mismatch:* Some highly educated individuals may find it difficult to match with jobs that fully utilize their qualifications, especially in niche or oversaturated fields. This can delay employment or lead to periods of job searching.

3. *Higher Expected Wages and Employer Reluctance:* Employers may be less willing to hire individuals with advanced degrees if doing so requires offering higher wages. This wage expectation can act as a barrier to hiring, particularly for roles that could be filled by candidates with lower credentials at lower cost.
4. *Supply-Side Competition:* An oversupply of graduates in certain fields may also suppress employment rates, as more individuals compete for a limited number of suitable positions, leading to underemployment or prolonged job search durations.

Hence, it is important to recognize that while higher educational attainment may lead to better income, it does not necessarily guarantee a higher employment rate. In conclusion, this is how we answer our null hypothesis.

H_0 : Wages **are strictly increasing** by post-secondary education attainment

H_A : ~~Wages **are not strictly increasing** by post-secondary education attainment~~

Although there are some small variation, the general result from the smoothing function shows that wages are monotonically increasing with respect to education attainment.

H_0 : ~~Employment rate **are strictly increasing** by post-secondary education attainment~~

H_A : Employment rate **are not strictly increasing** by post-secondary education attainment

As we can see from the graph above, employment rates are not strictly increasing by post-secondary education attainment due to the potential causes above.

5. Discussion and Future Extension

5.1 Strength and Limitation of Causal Method

The results offer insight into the causal effects of education on both employment probability and wage outcomes, estimated using an instrumental variables approach. Based on the graphs presented in Section 4, we successfully identify the Local Average Treatment Effect (LATE) for the compilers of our instrument—individuals who moved away from their home region to pursue higher education.

Below, we outline the key strengths and limitations of the causal methodology, as revealed through our empirical findings:

- Strong Instrument: The constructed IV shows a strong first-stage relationship with educational attainment, supported by high F-statistics even after adding controls.

- Controls for Key Confounders: The model controls for key confounders, reducing omitted variable bias. This is reflected in higher p-values after adding covariates, suggesting initial effects were partly due to confounding.

- Addresses Endogeneity: The use of an instrumental variable mitigates concerns about reverse causality and unobserved factors (e.g., ability, motivation) that could bias OLS estimates.

- Economic interpretability: Correct transformation of logit and log-wages into predicted probabilities and percentage increases enables more intuitive and interpretable results.

- Model Flexibility: Semi-parametric structure allows the model to have a more flexible causal interpretation for each level of education attainment.

Yet, the study also faces several methodological limitations.

- Binary IV: Using a binary instrumental variable to predict an ordinal-numeric treatment may oversimplify the relationship, potentially weakening the variation in predicted education levels and limiting the instrument's ability to fully capture differences across multiple categories.

- Imprecise Estimates for Higher Education Groups: lead to wider confidence intervals and less precise estimates for individuals with higher levels of education.

- LATE interpretation limits generalizability**:** Again, the causal finding from the result is only applicable to those who moved for education, but cannot generalized to the whole population.

- Trustworthiness of the IV: While the instrument proxies individuals who likely moved for educational purposes based on mobility patterns, it may misclassify those who moved for other reasons, potentially weakening the validity of the instrument.

These strengths and limitations should be kept in mind when interpreting the estimated effects and their implications for policy or broader labor market dynamics. In the next section, we will suggest future extensions to possibly match the result.

5.2 Future extension - A stronger IV

Despite the limitations of the causal methods in this paper, there is one simple IV that can resolve most of the limitations. A better-suited instrument would be "*proximity to the nearest post-secondary institution"*, which is a continuous variable in access to education compared to the binary "moved for education" variable. This alternative could strengthen the first-stage prediction and better capture variation across education levels, while still satisfying the core IV assumptions. Using proximity as an instrument could yield a LATE that generalizes to a broader group—namely, individuals who would attain higher education if access were easier—rather than just those willing to relocate. Making it more generalizable. Hence obtaining this IV in the model can resolve most of the limitations.

Why Not Use Proximity as an IV? While proximity-based IVs are powerful, they required a more detailed geographic data and advanced empirical work to link individuals to nearby post-secondary institutions. A key limitation of this study is the lack of access to exact residential addresses, which are restricted due to privacy concerns and would require higher-level data access permissions. Yet an individual Economist with higher access can practically take this plan into practice This extension represents a potential direction for future research using richer administrative data.

Another possible extension is to examine heterogeneous treatment effects by field of study and employment. Returns to education vary—STEM, business, or healthcare graduates often earn more than those in arts—due to differing market demand. Likewise, the same degree can yield different outcomes across sectors like public service or finance. Interacting predicted education with major and job sector can reveal these variations in educational returns.

6.Conclusion

This paper provides causal evidence on the impact of educational attainment on labor market outcomes using Canadian Census data and an instrumental variable approach. The results show that wages increase consistently with higher education, with the largest jump occurring at the Master's level. However, employment probabilities do not follow the same pattern and exhibit dips at certain advanced degrees. These findings support the idea that education enhances earning potential, but also reveal that higher attainment does not guarantee better employment outcomes. This highlights the complex relationship between education and work, shaped by both individual qualifications and broader labor market dynamics.

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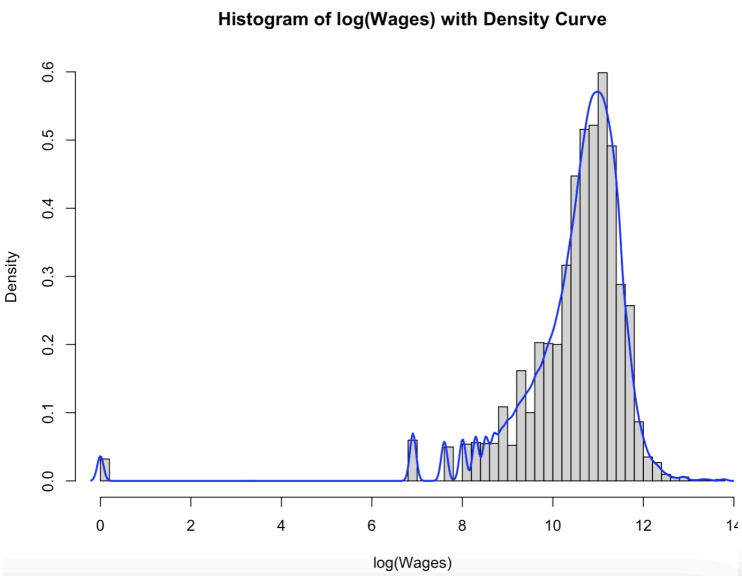
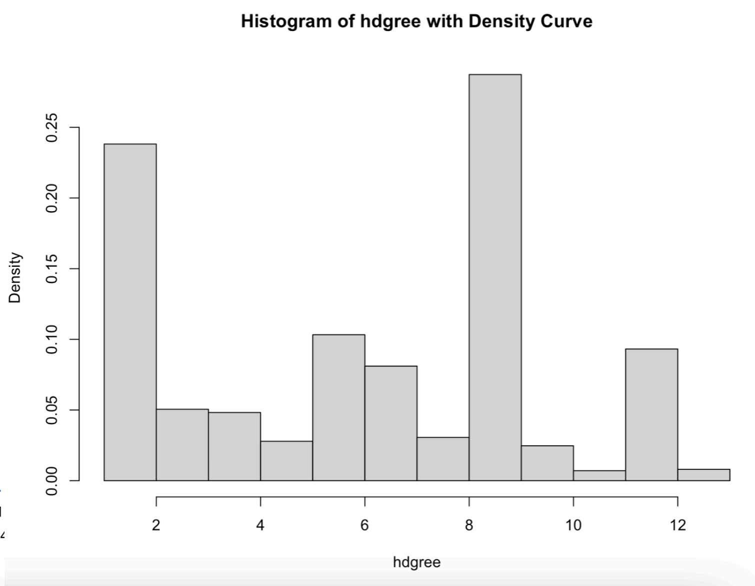
Use of AI disclaimer:

This paper has been constructed with the assistance of artificial intelligence, specifically ChatGPT-4o. AI was used to correct grammatical errors, enhance paragraph flow and readability, and assist with coding for data visualization, tables and graphs. However, the content, data filtering, analysis, interpretation of results, and all academic arguments presented originate from my own understanding, effort, and critical thinking.

Appendix 1: Summary Statistic for Key Variable and Prediction bins

Continous variables





Variable	Mean	Median	SD	Min	Max	N
hdgree	6.48	7	3.44	1	13 (Earned doctorate)	150,869
Wages	53,676	47,000	47,847	1	967,998	150,869

Categorical Variables (including predicted education values from stage 1)

Gender

Category	Count	Proportion
1	72,364	47.96%
2	78,505	52.04%

employment_status

Category	Count	Proportion
0	11,500	7.62%
1	139,369	92.38%

Citizen

Category	Count	Proportion
1	107,826	71.47%
2	19,753	13.09%
3	23,290	15.44%

Moved_for_studying

Category	Count	Proportion
0	137,190	90.93%
1	13,679	9.07%

Province (pr)

Category	Count	Proportion
10	1,652	1.09%
11	516	0.34%
12	3,584	2.38%
13	2,701	1.79%
24	34,937	23.16%
35	57,280	37.97%
46	5,302	3.51%
47	4,395	2.91%
48	18,909	12.53%
59	21,146	14.02%
70	447	0.30%

edu_hat_bins

Category	Count	Proportion
3	82	0.05%
4	10,188	6.75%
5	31,185	20.67%
6	43,168	28.61%
7	32,952	21.84%
8	17,968	11.91%
9	8,798	5.83%
10	4,558	3.02%
11	1,422	0.94%
12	488	0.32%
13	60	0.04%

CFInc

Category	Count	Proportion
1	110	0.07%
2	186	0.12%
3	142	0.09%
4	264	0.17%
5	217	0.14%
6	418	0.28%
7	373	0.25%
8	730	0.48%
9	1,943	1.29%
10	2,910	1.93%
11	3,643	2.41%
12	3,958	2.62%
13	4,219	2.80%
14	4,463	2.96%
15	4,624	3.06%
16	4,771	3.16%

17	4,868	3.23%
18	5,013	3.32%
19	5,071	3.36%
20	4,958	3.29%
21	5,045	3.34%
22	5,178	3.43%
23	5,092	3.38%
24	5,098	3.38%
25	9,741	6.46%
26	9,112	6.04%
27	8,306	5.51%
28	7,535	4.99%
29	6,636	4.40%
30	12,712	8.43%
31	8,220	5.45%
32	8,406	5.57%
33	6,907	4.58%

Appendix 2 : Raw model output and regression table

First stage

```
Call:
lm(formula = hdgree ~ Moved_for_studying + CFInc + Citizen +
    agegrp + Gender + pr, data = Census_coded)

Residuals:
    Min      1Q  Median      3Q     Max
-9.3401 -2.6369  0.2208  2.3710  9.3536

Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)         6.74316    0.30616  22.025  < 2e-16 ***
Moved_for_studying  2.74414    0.03193  85.943  < 2e-16 ***
CFInc2              0.50289    0.37236   1.351 0.176848
CFInc3             -0.15442    0.39321  -0.393 0.694536
CFInc4              0.58045    0.35129   1.652 0.098471 .
CFInc5              0.56456    0.36233   1.558 0.119197
CFInc6              0.08806    0.33173   0.265 0.790654
CFInc7             -0.18032    0.33587  -0.537 0.591369
CFInc8              0.19461    0.31665   0.615 0.538828
CFInc9             -0.07900    0.30347  -0.260 0.794610
CFInc10            -0.19402    0.30078  -0.645 0.518886
CFInc11            -0.25270    0.29969  -0.843 0.399118
CFInc12            -0.14767    0.29935  -0.493 0.621798
CFInc13            -0.11641    0.29912  -0.389 0.697143
CFInc14            -0.10972    0.29892  -0.367 0.713573
CFInc15             0.08949    0.29879   0.300 0.764559
CFInc16             0.17028    0.29869   0.570 0.568627
CFInc17             0.20970    0.29862   0.702 0.482542
```

```
CFInc18             0.30673    0.29855   1.027 0.304235
CFInc19             0.35184    0.29851   1.179 0.238537
CFInc20             0.31526    0.29859   1.056 0.291052
CFInc21             0.43140    0.29853   1.445 0.148434
CFInc22             0.60021    0.29846   2.011 0.044325 *
CFInc23             0.58356    0.29852   1.955 0.050603 .
CFInc24             0.60374    0.29852   2.022 0.043136 *
CFInc25             0.68704    0.29703   2.313 0.020722 *
CFInc26             0.87789    0.29717   2.954 0.003135 **
CFInc27             1.08523    0.29735   3.650 0.000263 ***
CFInc28             1.25600    0.29756   4.221 2.43e-05 ***
CFInc29             1.45548    0.29785   4.887 1.03e-06 ***
CFInc30             1.75080    0.29670   5.901 3.62e-09 ***
CFInc31             2.10443    0.29741   7.076 1.49e-12 ***
CFInc32             2.35409    0.29738   7.916 2.47e-15 ***
CFInc33             2.81407    0.29780   9.450  < 2e-16 ***
Citizen2            1.22704    0.02434  50.412  < 2e-16 ***
Citizen3            1.32227    0.02625  50.364  < 2e-16 ***
agegrp10            0.06105    0.01976   3.090 0.002003 **
agegrp11           -0.11818    0.02003  -5.899 3.66e-09 ***
Gender             -1.20366    0.01596 -75.403  < 2e-16 ***
pr11               -0.12919    0.15614  -0.827 0.408011
pr12                0.17408    0.09210   1.890 0.058761 .
pr13               -0.15394    0.09672  -1.592 0.111474
pr24                0.13323    0.07800   1.708 0.087607 .
pr35                0.38006    0.07745   4.907 9.24e-07 ***
pr46               -0.50473    0.08732  -5.780 7.48e-09 ***
pr47               -0.56630    0.08937  -6.337 2.36e-10 ***
pr48               -0.45489    0.07952  -5.720 1.07e-08 ***
pr59               -0.15918    0.07926  -2.008 0.044621 *
pr70               -1.39844    0.16514  -8.468  < 2e-16 ***
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 3.095 on 150820 degrees of freedom
Multiple R-squared:  0.1889,    Adjusted R-squared:  0.1886
F-statistic: 731.7 on 48 and 150820 DF,  p-value: < 2.2e-16
```

Second stage- Log wages

```
Call:
lm(formula = log(Wages) ~ edu_hat_bins + CFInc + Citizen + agegrp +
    Gender + pr, data = Census_coded)

Residuals:
     Min       1Q   Median       3Q      Max
-11.4396  -0.2474   0.2689   0.6018   5.2713

Coefficients:
                Estimate Std. Error t value Pr(>|t|)
(Intercept)     4.976686   0.177631  28.017  < 2e-16 ***
edu_hat_bins4   0.273746   0.134364   2.037 0.041617 *
edu_hat_bins5   0.362286   0.134412   2.695 0.007033 **
edu_hat_bins6   0.383840   0.134858   2.846 0.004424 **
edu_hat_bins7   0.363038   0.135496   2.679 0.007378 **
edu_hat_bins8   0.375757   0.136105   2.761 0.005767 **
edu_hat_bins9   0.498220   0.136422   3.652 0.000260 ***
edu_hat_bins10  0.526694   0.137357   3.834 0.000126 ***
edu_hat_bins11  0.497604   0.140347   3.546 0.000392 ***
edu_hat_bins12  0.704882   0.147785   4.770 1.85e-06 ***
edu_hat_bins13  0.892731   0.204666   4.362 1.29e-05 ***
CFInc2          1.480027   0.139628  10.600  < 2e-16 ***
CFInc3          1.907022   0.147448  12.934  < 2e-16 ***
CFInc4          2.023354   0.131743  15.358  < 2e-16 ***
CFInc5          2.055589   0.135874  15.129  < 2e-16 ***
CFInc6          2.314634   0.124378  18.610  < 2e-16 ***
CFInc7          2.469361   0.125944  19.607  < 2e-16 ***
CFInc8          2.532206   0.118727  21.328  < 2e-16 ***
CFInc9          2.704483   0.113796  23.766  < 2e-16 ***
CFInc10         3.125720   0.112796  27.711  < 2e-16 ***
CFInc11         3.538032   0.112401  31.477  < 2e-16 ***
CFInc12         3.734907   0.112258  33.271  < 2e-16 ***
```

```
CFInc13         3.924469   0.112171  34.987  < 2e-16 ***
CFInc14         4.023757   0.112095  35.896  < 2e-16 ***
CFInc15         4.086026   0.112036  36.471  < 2e-16 ***
CFInc16         4.088479   0.112000  36.504  < 2e-16 ***
CFInc17         4.114572   0.111972  36.746  < 2e-16 ***
CFInc18         4.141056   0.111945  36.992  < 2e-16 ***
CFInc19         4.168396   0.111934  37.240  < 2e-16 ***
CFInc20         4.198777   0.111959  37.503  < 2e-16 ***
CFInc21         4.274136   0.111940  38.182  < 2e-16 ***
CFInc22         4.277842   0.111925  38.221  < 2e-16 ***
CFInc23         4.300776   0.111948  38.418  < 2e-16 ***
CFInc24         4.345047   0.111948  38.813  < 2e-16 ***
CFInc25         4.402727   0.111399  39.522  < 2e-16 ***
CFInc26         4.472857   0.111482  40.122  < 2e-16 ***
CFInc27         4.540335   0.111597  40.685  < 2e-16 ***
CFInc28         4.612545   0.111695  41.296  < 2e-16 ***
CFInc29         4.667575   0.111832  41.737  < 2e-16 ***
CFInc30         4.772966   0.111477  42.816  < 2e-16 ***
CFInc31         4.864445   0.111846  43.492  < 2e-16 ***
CFInc32         4.956324   0.111892  44.296  < 2e-16 ***
CFInc33         5.043795   0.112147  44.975  < 2e-16 ***
Citizen2       -0.091692   0.010870  -8.435  < 2e-16 ***
Citizen3       -0.084746   0.013230  -6.405 1.50e-10 ***
agegrp10        0.140662   0.007416  18.967  < 2e-16 ***
agegrp11        0.211437   0.007551  28.002  < 2e-16 ***
Gender          0.380314   0.008494  44.775  < 2e-16 ***
pr11            0.085709   0.058541   1.464 0.143173
pr12            0.023193   0.034553   0.671 0.502078
pr13            0.104947   0.036279   2.893 0.003819 **
pr24            0.084708   0.029251   2.896 0.003781 **
pr35            0.074126   0.029093   2.548 0.010838 *
pr46            0.076410   0.032851   2.326 0.020021 *
```

```
pr47            0.114407   0.033643   3.401 0.000673 ***
pr48            0.154796   0.029902   5.177 2.26e-07 ***
pr59            0.130006   0.029725   4.374 1.22e-05 ***
pr70            0.241365   0.064274   3.755 0.000173 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.16 on 150811 degrees of freedom
Multiple R-squared:  0.2026,    Adjusted R-squared:  0.2023
F-statistic: 672.4 on 57 and 150811 DF,  p-value: < 2.2e-16
```

Second Stage - Logistic regression

Second stage regression - logistic regression on employment

```
Call:
glm(formula = employment_status ~ edu_hat_bins + CFInc + Citizen +
    agegrp + Gender + pr, family = binomial, data = Census_coded)

Coefficients:
                 Estimate Std. Error z value Pr(>|z|)
(Intercept)     0.0553735  0.4349213   0.127 0.898688
edu_hat_bins4   0.2085711  0.3312110   0.630 0.528876
edu_hat_bins5   0.4847084  0.3321231   1.459 0.144448
edu_hat_bins6   0.6502303  0.3343360   1.945 0.051794 .
edu_hat_bins7   0.6344421  0.3374034   1.880 0.060058 .
edu_hat_bins8   0.7015553  0.3398447   2.064 0.038985 *
edu_hat_bins9   0.9986228  0.3413970   2.925 0.003443 **
edu_hat_bins10  0.9241451  0.3458940   2.672 0.007545 **
edu_hat_bins11  0.7864693  0.3624353   2.170 0.030010 *
edu_hat_bins12  0.6040453  0.3997908   1.511 0.130813
edu_hat_bins13  2.0796340  1.0695251   1.944 0.051842 .
CFInc2          0.3573087  0.3466003   1.031 0.302590
CFInc3          0.0412382  0.3471919   0.119 0.905453
CFInc4         -0.1860255  0.3050845  -0.610 0.542027
CFInc5          0.0008841  0.3190452   0.003 0.997789
CFInc6          0.2115779  0.2973147   0.712 0.476694
CFInc7          0.0898487  0.2961190   0.303 0.761569
CFInc8          0.1684693  0.2807608   0.600 0.548476
CFInc9         -0.0612843  0.2667892  -0.230 0.818317
CFInc10        -0.0563762  0.2646460  -0.213 0.831307
CFInc11         0.1853468  0.2643690   0.701 0.483246
CFInc12         0.3976985  0.2646351   1.503 0.132886
CFInc13         0.5825862  0.2649734   2.199 0.027902 *
CFInc14         0.5973768  0.2647755   2.256 0.024060 *
CFInc15         0.8003902  0.2654521   3.015 0.002568 **
CFInc16         0.7062891  0.2649704   2.666 0.007686 **
```

```
CFInc17         0.7756616  0.2651413   2.925 0.003439 **
CFInc18         0.8176413  0.2651572   3.084 0.002045 **
CFInc19         0.7388803  0.2648754   2.790 0.005278 **
CFInc20         0.9858484  0.2659302   3.707 0.000210 ***
CFInc21         0.9673150  0.2658292   3.639 0.000274 ***
CFInc22         0.9723299  0.2658924   3.657 0.000255 ***
CFInc23         0.9802760  0.2659876   3.685 0.000228 ***
CFInc24         1.1178293  0.2666792   4.192 2.77e-05 ***
CFInc25         1.1150040  0.2638774   4.225 2.38e-05 ***
CFInc26         1.2731408  0.2649200   4.806 1.54e-06 ***
CFInc27         1.2679918  0.2655290   4.775 1.79e-06 ***
CFInc28         1.3422838  0.2664045   5.039 4.69e-07 ***
CFInc29         1.4819288  0.2680434   5.529 3.23e-08 ***
CFInc30         1.4874777  0.2654144   5.604 2.09e-08 ***
CFInc31         1.4966355  0.2678802   5.587 2.31e-08 ***
CFInc32         1.5677128  0.2682420   5.844 5.08e-09 ***
CFInc33         1.3574455  0.2690998   5.044 4.55e-07 ***
Citizen2       -0.1860339  0.0362933  -5.126 2.96e-07 ***
Citizen3        0.0269083  0.0429645   0.626 0.531123
agegrp10        0.0894663  0.0236726   3.779 0.000157 ***
agegrp11        0.1834172  0.0250788   7.314 2.60e-13 ***
Gender          0.2589442  0.0290207   8.923  < 2e-16 ***
pr11            0.8462194  0.2057839   4.112 3.92e-05 ***
pr12            0.0409854  0.0954208   0.430 0.667543
pr13            0.5630933  0.1085434   5.188 2.13e-07 ***
pr24            0.9151941  0.0831929  11.001  < 2e-16 ***
pr35            0.1462228  0.0811937   1.801 0.071717 .
pr46            0.6492325  0.0969239   6.698 2.11e-11 ***
pr47            0.6027350  0.1001382   6.019 1.75e-09 ***
pr48            0.3011990  0.0839745   3.587 0.000335 ***
pr59            0.6337120  0.0844059   7.508 6.01e-14 ***
pr70            0.5671341  0.2173991   2.609 0.009088 **
```

```
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 81304  on 150868  degrees of freedom
Residual deviance: 77577  on 150811  degrees of freedom
AIC: 77693

Number of Fisher Scoring iterations: 6
```

Appendix 3: Reference and Dictionary to Census data

hdgree (highest education attainment)

Code	Description	Unweighted	Weighted	Includes
1	No certificate, diploma or degree	131,882	4,884,572	
2	High (secondary) school diploma or equivalency certificate	218,657	8,098,267	
3	Non-apprenticeship trades	39,243	1,453,671	
4	Apprenticeship certificate	31,949	1,183,276	
5	Program of 3 months to less than 1 year (College, CEGEP and other non-university certificates or diplomas)	24,585	910,500	
6	Program of 1 to 2 years (College, CEGEP and other non-university certificates or diplomas)	72,844	2,697,817	
7	Program of more than 2 years (College, CEGEP and other non-university certificates or diplomas)	56,955	2,109,590	
8	University certificate or diploma below bachelor level	24,359	902,200	
9	Bachelor's degree	143,066	5,298,700	
10	University certificate or diploma above bachelor level	14,090	521,873	
11	Degree in medicine, dentistry, veterinary medicine or optometry	5,238	194,002	
12	Master's degree	46,471	1,721,170	
13	Earned doctorate	6,881	254,860	

Gender

Code	Description	Unweighted	Weighted	Includes
1	Woman+	496,738	18,397,732	
2	Man+	484,130	17,930,745	
	Total	980,868	36,328,477	

CFInc (Family Income)

1	Under $2,000	11,684	432,726
2	$2,000 to $4,999	3,188	118,072
3	$5,000 to $6,999	2,053	76,037
4	$7,000 to $9,999	4,023	149,000
5	$10,000 to $11,999	3,934	145,709
6	$12,000 to $14,999	6,306	233,558
7	$15,000 to $16,999	6,379	236,276
8	$17,000 to $19,999	8,941	331,153
9	$20,000 to $24,999	30,529	1,130,745
10	$25,000 to $29,999	25,346	938,750
11	$30,000 to $34,999	26,613	985,688
12	$35,000 to $39,999	30,958	1,146,618
13	$40,000 to $44,999	31,143	1,153,470
14	$45,000 to $49,999	30,586	1,132,839
15	$50,000 to $54,999	31,116	1,152,465
16	$55,000 to $59,999	31,269	1,158,133
17	$60,000 to $64,999	31,336	1,160,605
18	$65,000 to $69,999	31,058	1,150,311
19	$70,000 to $74,999	30,802	1,140,827
20	$75,000 to $79,999	30,476	1,128,742
21	$80,000 to $84,999	30,053	1,113,084
22	$85,000 to $89,999	29,750	1,101,862
23	$90,000 to $94,999	28,762	1,065,258
24	$95,000 to $99,999	27,944	1,034,969
25	$100,000 to $109,999	52,827	1,956,557
26	$110,000 to $119,999	48,634	1,801,256
27	$120,000 to $129,999	43,683	1,617,887
28	$130,000 to $139,999	39,014	1,444,967
29	$140,000 to $149,999	34,953	1,294,552
30	$150,000 to $174,999	69,453	2,572,308
31	$175,000 to $199,999	49,282	1,825,235

32	$200,000 to $249,999	56,193	2,081,162	
33	$250,000 and over	59,462	2,202,206	

pr: Province of residence

10	Newfoundland and Labrador	13,552	502,098	
11	Prince Edward Island	4,076	150,482	
12	Nova Scotia	25,789	955,820	
13	New Brunswick	20,511	759,158	
24	Quebec	224,250	8,308,479	
35	Ontario	378,849	14,031,754	
46	Manitoba	35,311	1,307,187	
47	Saskatchewan	29,764	1,103,275	
48	Alberta	112,878	4,177,717	
59	British Columbia	132,733	4,915,941	
70	Northern Canada	3,155	116,566	Yukon, Northwest Territories, and Nunavut

lfact: Labor market status

1	Employed - Worked in reference week	442,970	16,406,284	
2	Employed - Absent in reference week	24,106	892,834	
3	Unemployed - Temporary layoff - Did not look for work	11,087	410,630	
4	Unemployed - Temporary layoff - Looked for full-time work	8,626	319,469	
5	Unemployed - Temporary layoff - Looked for part-time work	2,470	91,479	
6	Unemployed - New job - Did not look for work	3,382	125,265	
7	Unemployed - New job - Looked for full-time work	2,800	103,698	
8	Unemployed - New job - Looked for part-time work	1,162	43,036	
9	Unemployed - Looked for full-time	16,382	606,710	

agegrp: Age group

9	25 to 29 years	64,759	2,398,480
10	30 to 34 years	67,392	2,495,961
11	35 to 39 years	67,606	2,503,890